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**A BIVARIATE AUTOREGRESSIVE INTEGRATED
MOVING AVERAGE ANALYSIS OF
COMBAT TROOP CASUALTY RATES**

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E. O'Donnell

C. G. Blood

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**NAVAL HEALTH RESEARCH CENTER
P. O. BOX 85122
SAN DIEGO, CALIFORNIA 92186 - 5122**

**NAVAL MEDICAL RESEARCH AND DEVELOPMENT COMMAND
BETHESDA, MARYLAND**



**A Bivariate AutoRegressive Integrated Moving Average
Analysis of Combat Troop Casualty Rates**

Edward O'Donnell *
Christopher G. Blood

Medical Information Systems and Operations Research Department

Naval Health Research Center

P.O. Box 85122

San Diego, CA 92186-5122

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SUMMARY

Problem

Mathematical modeling of medical resource requirements during military operations requires analyzing the underlying relationships between Disease and Non-Battle Injury (DNBI) rates and Wounded-In-Action (WIA) rates.

Objective

This analysis examines the underlying longitudinal aspects of WIA and DNBI incidence rates among combat troops deployed to Okinawa, Korea and Vietnam.

Approach

DNBI and WIA data were extracted from Marine Corps unit diaries for a 150-day period of the Korean War, a 90 day period of the Okinawa operation during World War II, and a 123 day period of the war in Vietnam. The time series data were set up in a bivariate autoregressive integrated moving average analysis.

Results

All the univariate models are best represented with a moving average term. The models for Okinawa and Korea fit in a AutoRegressive Integrated Moving Average [ARIMA(0,1,2)] and the Vietnam models fit an ARIMA(0,1,1). The DNBI series had significant predictive power from the WIA series on the same and following days.

Conclusion

This study demonstrates that WIA rates can be a useful predictor of DNBI rates when using a bivariate ARIMA model. High levels of WIA incidence will affect DNBI rates the immediate day and the following day. These results were consistent throughout the three military conflicts examined and should prove indicative for future military campaigns.

A Bivariate AutoRegressive Integrated Moving Average Analysis of Combat Troop Casualty Rates

Military medical planners need accurate predictions of both wounded-in-action (WIA) incidence and disease and non-battle injuries (DNBI) rates to determine the medical resources necessary to support a combat operation. Although there is much unpredictability surrounding these rates, this study will analyze WIA and DNBI rates from previous military operations and determine if mathematical modeling is possible. An analysis of these rates can start within a simple framework of a Poisson process. DNBI rates during a peacetime setting fit into a simple Poisson process where the variance is constant throughout the time interval¹. This framework, however, becomes inadequate when explaining arrival rates during a military conflict². Casualty admissions occur in batches and so a compound Poisson process was found to be more representative. Additionally, combat intensity varies during a conflict and so the casualty arrival rates will also have a non-stationary aspect throughout the conflict's time interval². Batch arrivals and non-stationary variance both violate simple queuing theory³ premises of 1) single arrivals and 2) a stationary variance with interarrival times described by an exponential distribution. These factors, therefore, suggest an alternative model be used.

The temporal nature of casualty occurrences indicate that a time series analysis may be appropriate. An initial analysis could involve separate univariate studies of WIA and DNBI rates from each conflict. However, the classical Box-Jenkins time series models⁴ are essentially devoid of explanatory power because they only describe certain empirical characteristics (such as trend or patterns) within a time series. Correlations between WIA and DNBI rates have been documented previously⁵. This research indicated that as battle intensity and casualties increase, there are associated rises in DNBI admissions attributable to increased battle fatigue and a lowering of immunological resistance levels among combat troops. To gain a better understanding of the relationship between WIA and DNBI rates, the estimation of covariance between the dependent variable (DNBI) and the explanatory variable (WIA) will be computed. A bivariate time series analysis between DNBI and WIA rates is appropriate because covariate analysis will be used to develop projections.

Historical data is available to study these daily relationships between the two series⁶. The

current study will initially examine the daily rates from each of the three military conflicts and look for trends within the series. Trends and patterns between each of the time series are also analyzed for future explanatory and predictive purposes.

Method

DNBI and WIA rates from each of the three conflicts are analyzed with the use of a bivariate *AutoRegressive Integrated Moving Average* (ARIMA) framework⁴. The two series will be set into a model with the WIA rates predicting the DNBI rates. This is similar to a linear regression function. The model will be in the form of a transfer function which will be used to explain and/or predict the output series (the DNBI series). The WIA series can also be used as a covariate to remove some of the noise (unexplained variation) of the DNBI series. This will yield an initial function:

$$Y_t = f(X_t) + N_t$$

where:

- Y_t is the DNBI series.
- X_t is the predictor WIA series.
- $f(X_t)$ is the transfer function to be modeled.
- N_t is the white noise process.

This analysis then can be broken into three main parts which will be implemented on each of the three different military conflicts⁶.

1. Examine the WIA and DNBI with time plots and then autocorrelation and partial autocorrelation plots to determine the appropriate transfer function.
2. After specifying the transfer function, calculate the residuals N_t .
3. Match an ARIMA model to the residuals and appraise the model.

The primary examination of the WIA and DNBI series is in the form of a Cross-Correlation Function (CCF). This is a device to graphically and statistically show the relationship between the predictor series (WIA) and the output series (DNBI). The series are set up in a daily format and so the CCF will show specific correlations among the two series on a daily basis with the appropriate direction and statistical significance. Prior to setting up

the CCF, the individual series must be examined for autocorrelation (or linear trend) within the series. This trend needs to be removed prior to setting up the CCF. The required filtering is accomplished using a differencing technique where the first observation is subtracted from the second, the second from the third and so on. This results in a new data series which is stationary and free from drift or linear trend. Removing or filtering the model of autocorrelation is the initial process of prewhitening. All of the series are non-stationary with autocorrelation and so a differencing term of one is set up for each series. This will yield:

$$w_t = (1 - B)^d X_t \quad \text{or: DNBI}_{t+1} - \text{DNBI}_t$$

$$z_t = (1 - B)^d Y_t \quad \text{or: WIA}_{t+1} - \text{WIA}_t$$

where:

w_t is the first ordered differenced term for the WIA series.

z_t is the first ordered differenced term for the DNBI series.

B is the ARIMA backshift operator.

d is the degree of differencing.

The backshift operator takes the series under study and shifts it back one time period. Taking the DNBI series for example: DNBI_{34} would be the DNBI data for the 34th day and $B(\text{DNBI}_{34})$ would be the same as DNBI_{33} . One of the main premises of time series analysis is that there are trends or patterns within the series itself. The backshift operator notation helps to explain these trends. A backshift operator of one lag can then be expressed as:

$$B(y_t) = Y_{t-1}$$

Trends within series may go back farther than one period and usually do with an exponentiated and decreasing effect which can then be shown as:

$$B^k(Y_t) = Y_{t-k}$$

The term of $(1-B)^d$ is denoted by: ∇^d . A simple autoregressive function $\text{AR}(p)$, depends only on past values of the series which can be set up as:

$$z_t = C + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \dots + \phi_p z_{t-p} + a_t$$

where:

C is a constant.

z_{t-1} are past values of the series.

ϕ_i are coefficients denoting the extent of lagged correlation.

a_t is a normally distributed white noise process.

ARIMA models may also include a moving average process. Θ represents the moving average term of the framework. This term shows the series can be described by a linear function of a few past shocks. A simple moving average model can be shown to be:

$$z_t = a_t - \Theta_1 a_{t-1} - \Theta_2 a_{t-2} - \dots - \Theta_q a_{t-q}$$

This is a moving average model of degree q or $MA(q)$ where:

z_t is a weighted average of the uncorrelated residuals.

Θ are the coefficients.

a_t are the uncorrelated residuals.

Combining the $AR(p)$ with the $MA(q)$ results in:

$$z_t = C + (\phi_1 z_{t-1} + \dots + \phi_p z_{t-p}) - (\Theta_1 a_{t-1} + \dots + \Theta_q a_{t-q}) + a_t$$

With the backshift operator the equation then is:

$$z_t = C + (\phi_1 B + \dots + \phi_p B^p) z_t + (1 - \Theta_1 B - \dots - \Theta_q B^q) a_t$$

Substituting $\forall y_t$ for z_t yields:

$$(1 - \phi B - \dots - \phi_p B^p) \forall y_t = C + (1 - \Theta_1 B - \dots - \Theta_q B^q) a_t$$

Since this notation is cumbersome, the $AR(p)$ term:

$$(1 - \phi B - \dots - \phi_p B^p) \text{ can be simplified to } \phi B.$$

The moving average term $MA(q)$:

$$(1 - \Theta_1 B - \dots - \Theta_q B^q) \text{ can be simplified to } \Theta B.$$

With all the appropriate substitutions, the general ARIMA model is then:

$$\phi B \forall y_t = C + \Theta B a_t$$

The appropriate ARIMA model can then be fitted to the WIA series so that it may be implemented into the transfer function. Making an initial assumption of no constant, the WIA series can be set up as:

$$w_t = \frac{\Theta(B)}{\Phi(B)} a_t$$

The inverse of the equation then yields the residuals:

$$a_t = \frac{\Phi(B)}{\Theta(B)} w_t$$

These residuals are then used to prewhiten or filter the z_t , which yields the prewhitened series b_t :

$$b_t = \frac{\Phi(B)}{\Theta(B)} z_t$$

The residuals (a_t) and the prewhitened series b_t can be put into a CCF that may be used to determine the transfer function. The expanded form of the general transfer function is:

$$f(X)_t = \frac{(U_0 + U_1 B + U_2 B^2 + \dots + U_p B^p)}{(1 - S_1 B - S_2 B^2 - \dots - S_r B^r)} X_{t-b}$$

The 'U' and 'S' parameters will be identified with the use of the CCF. The 'U' parameter shows up as spikes in the CCF plot and the 'S' parameter reveals exponential decay of the terms of the CCF. The transfer function is then set up as the explanatory/predictor variable in the original equation of:

$$Y_t = f(X_t) + N_t$$

This final model is then appraised for its predictive/explanatory capabilities and is tested for statistical significance.

Results

Okinawa Model

The analysis starts with the series from the Okinawa conflict. An AutoCorrelation Function plot (ACF) of the DNBI series indicates there is a spike at the first and the second day. The Partial AutoCorrelation Function (PACF) shows similar results. This information shows that a moving average parameter of order '2' is indicated. Because the series is non-

stationary throughout the time interval, it is differenced once. This results in an ARIMA(0,1,2) model. Results of this test show:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.2118	0.1041	2.03
2	DNBI	MA	2	0.2153	0.1040	2.07

The residual mean square for this model is 2.83 and the t-ratios show that the parameters are significant. The residuals were put into an ACF plot to determine if they were normally distributed with no significant correlations. They were found to be a white noise process with no significant correlations. The statistics and the plots then confirm the ARIMA(0,1,2) is adequate for the univariate Okinawa DNBI time series. The equation then is:

$$\nabla^1 y_t = C + (1 - \Theta_1 B - \dots - \Theta_2 B^2) a_t$$

The variance throughout the WIA time interval is non-stationary and so the time series needs to be differenced. The ACF and PACF plots revealed that a moving average parameter with order '2' is appropriate. The results for the univariate model are then:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	WIA	MA	1	0.3143	0.1039	3.03
2	WIA	MA	2	0.2125	0.1035	2.05

The t-ratios indicate the parameters are significant and the residual mean square is 18.35. The plot of the residuals does not produce a pure white noise process, but it is found to be the best of all possible models as compared to other variations on the theme. This results in the equation:

$$\nabla^1 y_t = (1 - \Theta_1 B - \Theta_2 B^2) a_t$$

With both the DNBI and WIA series adequately represented by ARIMA(0,1,2) models, the WIA series can be used as a covariate in the transfer function. The cross correlation function (CCF) between the two series indicates that there are strong correlations at days, 0,

1, 4 and 6. These spikes (hereafter U_t) show that the WIA series is influencing the DNBI series with the stated lag in days. This leads to the following model:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.3108	0.1064	2.92
2	WIA	U_t	- 6	-0.1101	0.0273	-4.03
3	WIA	U_t	0	0.1324	0.0391	3.38
4	WIA	U_t	1	-0.1178	0.0410	-2.87
5	WIA	U_t	4	0.0924	0.0306	3.07

The U_t terms were all significant and the original second order MA parameter was reduced to a first order term. After the DNBI series was filtered with the WIA series to reduce the white noise, the residual mean square was reduced from 2.83 to 2.43. This reduction of the residual mean square from the univariate to the bivariate model allows more accurate modeling. The final model for the transfer function is:

$$Y_t = U_6 + U_0 + U_1 + U_4 \frac{1 - \theta_1 B}{1 - B} a_t$$

Korean Model

Throughout the 150 days that encompass the DNBI series, there is a marked tendency for tempo swings. These varying intensity levels require that the series be smoothed. The ACF and PACF plots exhibit characteristics associated with a moving average process. Several preliminary models were set up and the resulting univariate model is thus:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.6747	0.0821	8.22
2	DNBI	MA	2	0.1672	0.0834	2.01

The initial residual mean square is 4.54 and the associated parameters are statistically significant. Plots of the residuals reveal that the process is indeed white noise and so the ARIMA(0,1,2) model is accepted. The univariate DNBI model is:

$$\nabla y_t = (1 - \Theta_1 B - \Theta_2 B^2) a_t$$

After differencing the WIA series and examining the ACF and PACF plots, the initial model is set up below:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	WIA	MA	1	0.6174	0.0497	12.43
2	WIA	MA	2	0.3756	0.0678	5.54

The resulting residuals form a white noise process and the t-ratios indicate statistical significance. The residual mean square for the WIA ARIMA(0,1,2) model is 68.29. This equation is expressed as:

$$\nabla y_t = (1 - \Theta_1 B - \Theta_2 B^2) a_t$$

The WIA model is then used to filter the DNBI model to reduce the amount of noise within the series. The associated CCF plot indicates that there are U_t terms at days "0" and "1". The form of these terms demonstrates that there is an exponential decay identified. An appropriate term (S_t) is put into the model to accommodate this effect.

The final model is then:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.9724	0.0197	49.26
2	WIA	U_t	0	0.0582	0.0113	5.16
3	WIA	U_t	1	-0.058	0.0111	-5.22
4	WIA	S_t	1	0.8088	0.063	12.83

The U_t and S_t terms were all significant and the original second-order MA parameter was reduced to a first order term. After the DNBI series was filtered with the WIA series to

reduce the white noise, the residual mean square was reduced from 4.54 to 3.87. Adding the WIA series as a covariate helped to reduce the amount of noise and so it is kept in the final model. The transfer function can be expressed as:

$$Y_t = \frac{U_0 + U_1}{1 - S_r} + \frac{1 - \Theta_1 B}{1 - B} a_t$$

The plotted residuals indicate a white noise process. The residuals of the WIA univariate model were put into a CCF with the residuals of the transfer function and no significant correlations were found. This model is accepted as the best available.

Vietnam Model

As was the case with the preceding military conflicts, the Vietnamese war was subject to varying levels of fighting and the resulting series is non-stationary. Consequently, a differencing term of the first order was used. Examination of the ACF and PACF plots demonstrate a moving average process. There is one initial spike in the ACF and a decaying process with the PACF starting in the first or second day. After experimenting with several alternatives, the following results are tabulated:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.9820	0.0156	62.87

The use of only one moving average parameter provided the lowest residual mean square of 3.83 and also residuals that were normally distributed as a white noise process. This simple univariate model is stated as:

$$\nabla y_t = (1 - \Theta_1 B) a_t$$

The WIA series was modeled in the same way as the DNBI series. First order differencing and a single moving average parameter result in:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	WIA	MA	1	0.9660	0.0221	43.64

A second order moving average term was entered but was deemed inadequate. This model produced the lowest residual mean square of 10.82 and the residuals were normally distributed with zero mean and unit variance. The appropriate equation is:

$$\nabla^2 y_t = (1 - \Theta_1 B) a_t$$

Using the residuals of the WIA model and the prewhitened DNBI residuals, a CCF plot is examined to find the 'U' and 'S' parameters. A single order moving average term is also used to present the final model:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.9835	0.0065	151.44
2	WIA	U_t	0	0.1266	0.0532	2.38
3	WIA	U_t	1	-0.1245	0.0535	-2.33

Two spikes at day "0" and day "1" indicate that two U_t are appropriate. The moving average of order one is statistically significant with a very high t-ratio. The resulting residual mean square is 3.66, while the original univariate was 3.82. While not a large decrease, both the U_t parameters are statistically significant. Further plots of the residuals reveal a white noise process and the CCF between the predictor residuals and the transfer function residuals show no correlations and so the model is accepted.

The final equation is then:

$$Y_t = U_0 + U_1 + \frac{1 - \Theta_1 B}{1 - B} + a_t$$

Pooled Time Series Model

The three models have significant similarities. They all have differencing terms of '1' and a moving average parameter of order '1' or '2'. These similarities allow the idea of pooling the series into one model and testing its significance. Dummy variables were entered into the pooled model to test for homogeneity of slope between the three military conflicts. An analysis of covariance was also tested. Both tests revealed that pooling the data is justified because there is homogeneity of slopes between the three military operations. With

the pooled time series data, the best empirical model is then:

Parameter	Variable	Type	Order	Estimate	Std. Error	T-ratio
1	DNBI	MA	1	0.6637	0.0522	12.69
2	DNBI	MA	2	0.1131	0.0523	2.16
3	WIA	U_t	0	.0815	0.0169	4.79

All the variables are significant and the residual mean square is 4.01. The equation for the pooled model is then:

$$Y_t = U_0 + \frac{(1 - \theta_1 - \theta_2 B^2)}{1 - B} a_t$$

Conclusions

This study has attempted to explain and predict DNBI rates during a military conflict. During a peacetime scenario, DNBI incidence follows a simple Poisson process with interarrival times represented by an exponential distribution. However, during military conflicts the DNBI rates change markedly. This study has shown that the level of conflict significantly influences the level of disease and non-battle injuries sustained by the soldiers. This in turn will influence the entire patient load that a military treatment facility handles. When there is a peak in WIA incidence, there is an associated projected peak in DNBI incidence.

Each of the three conflicts analyzed possessed significantly different operational characteristics. However, they all exhibited very similar statistical traits. Each of the univariate models were best represented by a moving average parameter of order one or two and all had a differencing term of order one. A significant finding comes from the bivariate models. Initial examination of the correlation between the series indicates that WIA has a strong influence on the DNBI rates of the same day and declines thereafter. Depending on which conflict is being analyzed, the correlations are evident up to seven or more days.

Autocorrelation within each series must be removed to determine the true relationship between WIA and DNBI. Filtering the series reveals the correlations between DNBI and WIA do not extend for multiple day periods. After the autocorrelation was filtered out and the final transfer function was set up, it was determined that each of the models had leading indicators at days "0" and day "1". This shows that while WIA incidence is a statistically indicative variable in predicting DNBI, the casualty levels will influence DNBI only on the same day and the day following. While there were several other significant terms within the transfer function, the two leading daily indicators were present among all three conflicts.

DNBI rates cannot be forecast by a simple mean rate that remains constant. Even during peacetime situations the arrival process is random, and, during military operations the rates are further influenced by the exogenous forces of the ongoing battle. Examination of the trends underlying casualty and disease rates during combat operations allows mathematical modeling of medical admission incidence. The pooled time series model yields information critical to modeling these admission rates. Pooling all the data into a single model allows a generalized projection system to be set up. With different parameters specifying various hypothetical combat scenarios, a forecasting tool to simulate WIA incidence can be developed, which in turn will allow projections of DNBI incidence. Through these simulations, not only can the overall patient load be anticipated, the size, frequency, and distribution of peak patient loads can be determined. This data will allow planners to program the resources needed for the expected patient load and to provide the capacity to absorb the periodic influxes that are expected to occur.

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